An Enhanced Segmentation of Blood Vessels in Retinal Images Using Contourlet

S. H. Rezatofighi[1], A. Roodaki[1], H. Ahmadi Noubari [1,2]
[1] Dept. of Electrical and Computer Engineering, University of Tehran, Iran, [2] University of Tehran and University of British Columbia, Canada

Abstract—**Retinal images acquired using a fundus camera often contain low grey, low level contrast and are of low dynamic range. This may seriously affect the automatic segmentation stage and subsequent results; hence, it is necessary to carry-out preprocessing to improve image contrast results before segmentation. Here we present a new multi-scale method for retinal image contrast enhancement using Contourlet transform. In this paper, a combination of feature extraction approach which utilizes Local Binary Pattern (LBP), morphological method and spatial image processing is proposed for segmenting the retinal blood vessels in optic fundus images. Furthermore, performance of Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multilayer Perceptron (MLP) is investigated in the classification section. The performance of the proposed algorithm is tested on the publicly available DRIVE database. The results are numerically assessed for different proposed algorithms.**

I. Introduction

ADVANCE symptoms of systematic diseases such as diabetics may be diagnosed by the assessment of retinal images and retinal blood vessels [1]. In vivo non-invasive study of the influence of the factors that affect the human body vasculature may also be carried-out through a window called eye. Furthermore, inspection of optic fundus photographs [1], [4], and flourocein images [2] may also help to diagnose and monitor the progress of general diseases such as diabetes, hypertension, arteriosclerosis, cardiovascular diseases, stroke and eye diseases like retinopathy of prematurity [1]-[3]. Hence, the measurement and analysis of retinal blood vessels is of diagnostic value for a wide range of pathological states. However, manual analysis of the complex retinal blood vessel trees in fundus images is a time-consuming task, and as the number of images increases, the study becomes formidable. Furthermore, the manually segmented images suffer from variability of diagnostic results both inter-observer and intra-observer variations.

For automatic assessment of retinal images, segmentation of the vessels from the background is considered as an initial requirement. However since the retinal images acquired with a fundus camera often are characterized with low grey level contrast and low dynamic range, problem may seriously affect the automatic segmentation results. Therefore it is necessary to carry-out contrast enhancement as part of the required preprocessing steps in particular for those cases when the original retinal image is considered not a good candidate to yield the desired segmentation.

Several techniques have been proposed for improving the quality of the retinal images. Recently, the wavelet transform has been widely used in the medical image processing. [5] introduced a fast discrete wavelet transform algorithm which is used in several applications [6]-[8]. The wavelet transform is a type of multi-scale analysis that decomposes input signal into high frequency details and low frequency approximation component at different resolutions. To enhance the features, the selected detail coefficients are adjusted by multiplication with an adaptive gain value. The enhanced image is then reconstructed using adjusted wavelet coefficients. The Curvelet [9] and Contourlet [10] transforms are two examples of geometrical transforms developed for sparse representation of natural images. Both of these transforms offer two important features i.e. anisotropy scaling law and directionality; they are considered as good choices for edge enhancement applications. In [10] a double filter banks structure for implementation of Contourlet transform was developed and was used for nonlinear approximation and de-noising application,. Since the Contourlet transform has the capability of representing edges and textural information of natural images, it is considered suitable for representation of lesions and blood vessels of a retinal image. [11] employed Contourlets for improving the enhancement of these images and compared the results with other methods

Several other automatic algorithms have also been proposed for the segmentation of retinal blood vessels. According to [5], methods for detecting blood vessels generally fall into three main categories: 1) kernel-based, 2) tracking based and 3) classifier-based. Kernel-based methods convolve a kernel with the image based on a predefined model. For instance, in [13] Gaussian shaped curves are used to model the cross section of a vessel after which a matched filter is used for detection. These techniques are fast when used with small kernels. However, as the kernels size

Manuscript received April 12, 2008.
Authors are with Control and Intelligent Processing Center of Excellence,, Faculty of Electrical and Computer Engineering, University of Tehran, Corresponding author: H.Ahmadi-Noubari, Dept.of Electrical and Computer Engineering, University of British Columbia, Canada, Tel 011-98-914-3164760, email (noubari@ece.ubc.ca)
S.H Rezatofighi[1]e-mail: (h.tofighi@ece.ut.ac.ir)
A. Roodaki[1] email: (a.roodaki@ece.ut.ac.ir).

become larger and noting that the rotational invariance requires several rotated kernels to be used, the performance of the algorithms deteriorates considerably.. Tracking methods use a model to track the vessels. These methods start with certain seed points which may be set manually by simple thresholding or by morphological operations [1].

In classifier-based methods, various types of features are extracted from the image and the feature vectors are then introduced to the classifier to assign the corresponding pixel to a certain class or segment of the image. For example, in [4], wavelet transform features of an image are extracted and a Gaussian mixture model classifier is used for classification.

In this paper, the Contourlet enhancement method [11] is employed for improving the automated segmentation of blood vessels. The main reason for choosing this method is its performance in enhancing the capillary vessels which is considered an essential factor for improving the segmentation result. We then apply, Local Binary Pattern (LBP) [14] as part of feature extraction step. In the sequel, Multi Layer Perceptron Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference System (ANFIS) are employed for segmentation of blood vessels from the background image.

Recently, LBP is used in many applications such as characterizing arteries plaque compositions in Intravascular Ultrasound (IVUS) images [15]. The reason for its superior performance is due to the fact that features extracted in this method are rotation and gradient invariant. Also, in [14], [15], they have reported that these features lead to computationally more efficient results in comparison with other textural features such as co-occurrence.

A brief introduction to Contourlet transform, LBP, ANFIS, and MLP is provided in section II. In Section III segmentation algorithm and post-processing step to improve the results are presented. The experimental results of the proposed method are presented in section IV. Finally, section V concludes the paper.

II. Methodology

A. Preprocessing

We have considered Contourlet enhancement algorithm as a preprocessing step. In this method, the Contourlet coefficients are modified via a nonlinear function in which the estimated noise is taken into consideration to increase the accuracy of reconstruction and to improve visualization [16], [17]. Enhancing through Contourlet method was implemented in five steps as follows:

1) Extracting the green channel from color retinal image which provides the highest contrast between vessels and background [10].
2) Calculating the Contourlet transform of the input image
3) Calculating noise standard deviation σ_j for each subband of the Contourlet transform.
4) Multiplying each Contourlet coefficient $C_{j,k}$ by a nonlinear function that is determined by the standard deviation of the noise in the corresponding subband and absolute amplitude of each coefficient.
5) Reconstructing the enhanced image from the modified Contourlet coefficients.

For the Contourlet transform, we use five LP levels and 32 directions at the finest level. In the LP section, the ''9–7'' filters was partly chosen because of their linear phase property, an important factor in image processing. In the DFB section, the ''pkva'' filters was used. The algorithm proposed in [18] was employed for estimating the standard deviation of the noise in each band.

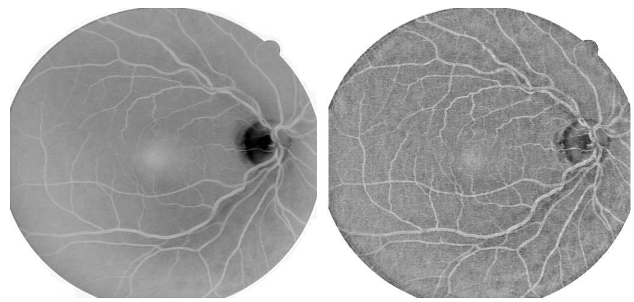

Fig. 1. The inverted green channel (left) and its corresponding enhanced image using Contourlet enhancement algorithm (right).

As illustrated in Fig. 1, excellent results were obtained by applying Contourlet enhancement algorithm. This was more so in capillary vessels The proposed enhancement was also able to improve the results of the segmentation section as discussed below.

B. Local Binary Pattern

Local Binary Patterns (LBP) refers to structure related measures [16]. The operator detects "uniform" local binary patterns within circularly symmetric neighborhoods of P members on a circle of radius R which is given by $LBP_{R,P}^{riu2}$. Some neighbor sets are shown in Fig. 2.

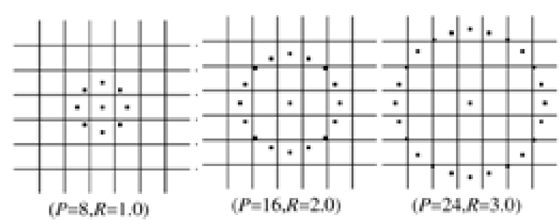

Fig. 2. Circularly symmetric neighbor sets for different (P,R).

In addition to $LBP_{R,P}^{riu2}$, which is rotation and gray-scale invariant, the $VAR_{P,R}$, consider the variation of gray-scales in that region, as well as the decimal representation of the binary sequence are extracted from every circle.

C. Adaptive Neuro-Fuzzy Inference System

This network is a Sugeno type model with ability of being trained in which x and y are considered as networks inputs

and where if-then rules are applied as follows:
Rule 1: If (x is $A1$) and (y is $B1$) then ($f1 = p1x + q1y + r1$)
Rule 2: If (x is $A2$) and (y is $B2$) then ($f2 = p2x + q2y + r2$)
where A and B are two fuzzy sets. This system is shown in Fig. 3.

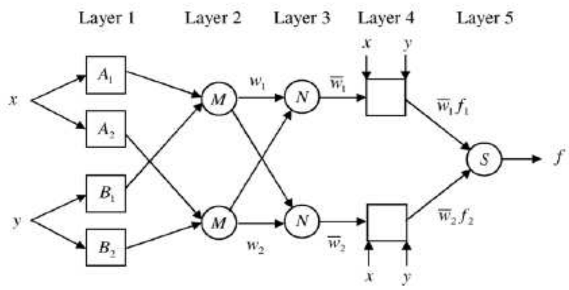

Fig. 3. A typical two input ANFIS.

This system is considered to have two kinds of nodes. The inputs depicted by rectangles, represent the nodes that contain parameters that are to be trained with the learning algorithm while circles represent the nodes that are constant and don't contain any parameters.

The first layer consists of adaptive neurons. These nodes are used to determine the extent of membership to each fuzzy set. Parameters of these nodes are the same as the parameters of different membership functions which are set to be Gaussian in this study. The second layer consists of constant nodes which simply perform the logical AND in premise part of the if-then rules. Multiplication is considered as logical AND in our model. The third layer consists of constant nodes normalizing the outputs of the previous layer. The fourth layer composed of adaptive neurons which compute a linear function of the outputs of previous layer where the parameters of these functions are trained during the training process.

The learning method of this network is referred to as Hybrid method. In this learning method, first the parameters of the neurons in the first layer are considered to be constants having initial random values. Then the parameters of neurons in the fourth layer are trained with a LMS algorithm. In the next step these trained parameters are considered as constant values and the parameters of neurons of the first layer are trained with an error back propagation algorithm. These steps are iterated till the condition for stopping rule is satisfied.

The inputs to this network are six features that are extracted with LBP method from the 5*5 windows and where three fuzzy sets are considered for each input. An output neuron is also considered in the network used in this study. Network output 1 is used for the decision of the network for the case when the pixel belongs to vessel class where the output -1 implies that the pixel is obtained from background.

D. Multilayer Perceptron

In this part of the study, a multilayer perceptron network with one hidden layer is considered. The number of neurons in the hidden layer is empirically set to five and a single neuron is considered in the output layer. Output is 1 is used for the decision of the network when the pixel belongs to vessel class and the output -1 implies that the pixel is obtained from background.

III. Segmentation and Post-processing

In this section, our proposed algorithm for retinal blood vessel segmentation is explained. First, the region defined by the mask, which is a binary image provided to determine the working area of study, in every image is swept by a 5*5 window in which two circles with radii of one and two are considered in each window. Three different features are extracted from each circle; in this case, we benefit from multi resolution characteristic of LBP. These features consist of $LBP^{riu2}_{R,P}$, $VAR_{R,P}$, and decimal representation of the binary sequence. As such, there are six features that are assigned to each pixel. For comparison of features with values that may vary considerably, the feature vectors have to be normalized before classification section.

In the next step, normalized feature vectors are used as inputs to the classifiers. Here, the MLP and the ANFIS networks are used as classifiers.

Often these images are contaminated with noise where the presence of noise and contrast variations, may result in falsely detected blood vessels. To eliminate or reduce these errors, the following post-processing step is applied.

We use morphological operations including erosion and dilation in the post-processing step. First, the image is eroded using a structural element of a certain size. Next, connected components smaller than a specified size are removed. Finally the image is dilated using the same structural element that was used for eroding.

IV. Experimental Results

Our proposed method was tested on images from publicly available DRIVE database [19]. The DRIVE database contains 40 color images of the retina, with 565 × 584 pixels and 8 bits per color channel, in LZW compressed TIFF format. The images were originally captured by a Canon CR5 nonmydriatic 3 charge-coupled device (CCD) camera and were initially saved in JPEG-format. The database also includes binary images which are obtained using manual segmentation. These binary images have been used as ground truth for performance evaluation of several vessel segmentation methods [1]. The 40 images were divided into a training set and a test set by the authors of the database. The results of the manual segmentation are available for all the images of the two sets. For the images of the test set, a second independent manual segmentation also exists.

For validation of the methods used in this paper, the accuracy, True Positive Ratio (TPR), and False Positive Ratio (FPR), were computed for each method. For the accuracy we used the ratio of the total number of correctly classified points (sum of true positives and true negatives) by the number of nonblack points within the mask. The ground proof for computing the performance measures was the manual segmentation result. The values for the fraction of pixels erroneously classified as vessel pixels, (FPR), and for the percentage of pixels correctly classified as vessel pixels, (TPR), are also reported. Twenty images in the test set of DRIVE database were chosen for testing the methods. First, the Contourlet enhancement algorithm was applied on every image. Then, the first image of the training set and its corresponding characterized image by the first manual were used for training the networks. Next, the extracted features from each image of the test set are classified by the trained networks. In the sequel, the post-processing algorithm is applied on the constructed images (see Fig. 4). Table 1 shows the results of our experiments.

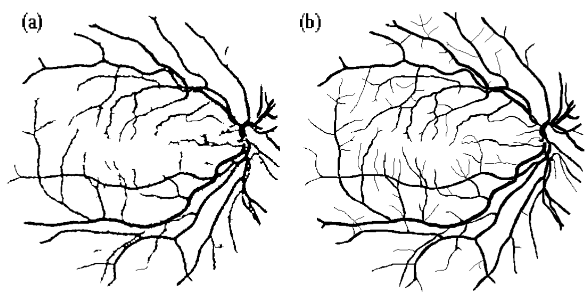

Fig. 4. Result of proposed algorithm using ANFIS classifier (left) and result of human observer (right).

TABLE I
RESULTS OF VESSEL SEGMENTATION METHODS

Method	accuracy	TPR	FPR
2nd human observer	0.9473	0.7761	0.0275
MLP(without enhancement)	0.9221	0.6944	0.032
ANFIS(without enhancement)	0.9352	0.7116	0.0291
MLP(Contourlet enhancement)	0.9355	0.7223	0.0289
ANFIS(Contourlet enhancement)	0.9410	0.7308	0.0277

V. DISCUSSION AND CONCLUSION

We have used the advantages offered by Contourlet in detection and enhancement of contours and edges. Using Contourlet, as indicated by capability to improve the edges of capillary vessels, considerable improvement was achieved for the low dynamic range and low contrast images. Furthermore, reducing the noise in the fovea and blind spot areas enabled us to obtain much improved results as compared with methods without applying enhancement algorithms.

The ground truth in this study was provided by an expert opinion. In fact, experts characterize images without paying much consideration of quantitative variations of every pixel where the trace of capillary vessels is estimated. As such better performance was achieved with ANFIS classifier in comparison with MLP.

REFERENCES

[1] M. G Mendonça and A. Campilho, "Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction," *IEEE Trans. Med. Imag.,* vol. 147, pp. 1200—1213, 2006.

[2] M. E. Martinez-Prez, A. D. Hughes, S. A. Thom, A. A. Bharath, and K. H. Parker, "Segmentation of blood vessels from Red-Free and fluoroscein retinal images," *Med. Image. Anal.,* vol. 11, pp. 47—61, 2007.)

[3] K. A. Vermeer, F. M. Vos, H. G. Lemij, and A. M. Vossepoel, "A model based method for retinal blood vessel detection," *Comput. Biol. Med.,* vol. 34, pp. 209—219, 2004.

[4] J. V. B. Soares, J. J. G. Leandro, R. M. Cesar Jr., H. F. Jelinek, and M. J. Cree, "Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification," *IEEE Trans. Med. Imag.,* vol. 25, pp. 1214—1222, 2006.

[5] S.G. Mallat, "A theory for multi-resolution signal decomposition: the wavelet representation," *IEEE Trans. Pattern Anal. Machine Intelligence.,* vol. 11, no. 7, pp. 674–689, 1989.

[6] A. Laine and S. Song, "Multiscale wavelet representations for mammographic feature analysis," *In: Proc. SPIE Conf. on Mathematical Methods in Medical Image.* vol. 1768, pp. 306–316, 1992(a).

[7] A. Laine and S. Song, "Wavelet processing techniques for digital mammography," *In: Proc. SPIE Conf. on Visualization in Biomedical Computation,* vol. 1808, pp. 610–624, 1992(b).

[8] A. Laine, S. Schuler, J. Fan, and et al., "Mammographic feature enhancement by multiscale analysis," *IEEE Trans. Med. Imaging*, vol. 13, no. 4, pp. 725–740, 1994.

[9] E. J. Cande`s and D. L. Donoho (1999). Curvelets—a surprisingly effective nonadaptive representation for objects with edges. Available: http://www.acm.caltech.edu/~emmanuel/publications.html.

[10] M. N. Do and M. Vetterli, "The Contourlet transform: an efficient directional multiresolution image representation," *IEEE Trans. Image Process.,* vol. 14, no. 12, pp. 2091–2106, 2005.

[11] P. Feng, Y. Pan, B. Wei, W. Jin, and D. Mi, "Enhancing retinal image by the Contourlet transform," *Pattern Recogn. Lett.,* vol. 28, pp. 516—522, 2007.

[12] A. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," *IEEE Trans. Medical Imaging.,* vol. 19, pp. 203—219, 2000.

[13] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using Two-Dimensional matched filters," *IEEE Trans. Med. Imag.*, vol. 8, pp. 263—269, 1989.

[14] T. Ojala, M. PietikaÈ inen, and T. MaÈenpaÈa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Trans. Pattern Anal. Machine Intelligence*, vol. 24, no. 7, 2002.

[15] K. L. Caballero, J. Barajas, O. Pujol, J. Mauri, and P. Radeva, "In-vivo IVUS tissue classification a comparison between normalized image reconstruction and RF signals analysis," *11th Iberoamerican Congress on Pattern Recognition (CIARP'06)*, 2006.

[16] K. V. Velde, "Multi-scale colour image enhancement," *In: IEEE Internat. Proc. Image Process.,* vol. 3, pp. 584–587, 1999.

[17] J. L. Starck, M. Murtagh, E. J. Cande`s, and D. L. Donoho, "Gray and color image contrast enhancement by the curvelet transform," *IEEE Trans. Image Process.* vol. 12, no. 6, pp. 706–717, 2003.

[18] D. L. Donoho, "Denoising by Soft thresholding," *IEEE Trans. Information Theory,* vol. 41, no. 3 , pp. 613-627, May 1995.

[19] M. Niemeijer, B. vanGinneken, , (2002) [Online]. Available: http://www.isi.uu.nl/Reseach/Databases/DRIVE/results.php.